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On March 30-April 1, 2011 the U.S. Department of Homeland Security, Science and Technology Directorate (S&T), Office of University Programs (OUP) hosted the Fifth Annual DHS University Summit at the Washington, DC. Renaissance Hotel. The Summit theme was "Transportation: Catastrophes and Complex Systems", and provided an opportunity to learn about cutting-edge homeland security science and technology research related to transportation systems.

Conference attendees included researchers and innovators in academia, industry, and government; chief scientists, program analysts, portfolio managers, and other subject matter experts; federal, state, and municipal employees; first responders; DHS operators; and academic institutions associated with the twelve DHS-sponsored research Centers of Excellence (COE) and their students.

As part of the Summit, OUP invited student researchers from the DHS Centers of Excellence to submit abstracts on their projects. Presenters were selected by DHS subject matter experts and invited to participate in the Summit. The papers published in this special supplement to Homeland Security Affairs, which summarize the work presented by the student participants, were recognized for providing significant findings, indications and potentially important contributions to the homeland security science and technology enterprise.

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Vocal Analysis Software for Security Screening: Validity and Deception Detection Potential

Aaron C. Elkins, Judee Burgoon, and Jay Nunamaker

ABSTRACT

Our voices are encoded with emotional information. While it is complex and difficult to develop software to classify emotion and deception from the voice, it is possible. Using experimental methods, this research examines current commercial vocal analysis software for predictive and statistical validity in identifying emotion and deception for security screening. It is unrealistic to rely completely on the voice to detect deception and hostile intent for all people and all situations. But, by exploring the vocal variables used by the software, we are able to correspond and fuse them with other detection technologies for higher prediction reliability and accuracy. Implementing an unreliable and invalid detection technology could place the country's security in jeopardy by failing to detect actual threats. Just as deleterious, however, would be to dismiss technology, such as vocal analysis, before it has been thoroughly examined. This would deprive us of a valuable tool for detecting threats and securing our homeland.

INTRODUCTION

Imagine a time when a close friend or parent spoke to you. In the case of your parent, you knew immediately if they were angry or happy with you from their voice alone. Your parent spoke louder, faster, and in a higher pitch than usual after discovering you broke her grandmother's vase. Contrast this with a close friend who recently had a death in his family. He sounds depressed and speaks much slower and in a lower volume then an angry parent. With the thoughts of their loved ones on their mind people would sound distracted, with shorter responses and vocal interruptions. As social creatures, we can quickly and automatically determine emotional state or mood from the voice.

Despite how effortlessly we can interpret emotion and mood from the voice, developing computer software to replicate this feat is exceedingly difficult. Computers require very specific and predictable inputs and cannot deal well with unbounded contexts and the chaotic nature of conversation. We take for granted how complex conversations are and how quickly they branch and weave back and forth between topics and ideas. We even alternate between moods and emotions in just one conversation, from anger when recounting a mean boss to happiness when discussing an upcoming birthday party.

In addition to the complexity of conversation contexts, the science of measuring and classifying emotion and deception using the voice is in its infancy. Fear, for instance, is characterized as fast speech rate, higher mean pitch, low pitch variability, and lower voice quality.[1] However, the relationship between vocal measures and emotion has not been well explored beyond correlational analyses, leading to conflicting results and alternative vocal profiles for fear.[2]

Previous research has found that an increase in the fundamental frequency or pitch is related to stress or arousal.[3] Pitch is a function of the speed of vibration of the vocal chords during speech production.[4] Females have smaller vocal chords than men, requiring their vocal chords to vibrate faster and leading to their higher perceived pitch. When we are aroused our muscles tense and tighten. When the vocal muscles become tenser they vibrate at a higher frequency, leading to a higher pitch. Similarly, previous research has found that when aroused or excited, our pitch also exhibits more variation and higher intensities.[5]

Deceptive speech is also predicted to be more cognitively taxing, leading to non-strategic or leakage cues.[6] These cues, specific to cognitive effort, can be measured vocally. Cognitively-taxed speakers take longer to respond (response latency) and incorporate more nonfluencies (e.g., "um" "uh", speech errors).

DISCUSSION

STATE THE PROBLEM

Despite the complexity of communication and the dearth of research in classifying emotion and deception from the voice, commercial software for automatically detecting emotion, stress, and deception is being adopted for use in law enforcement, fraud detection, and rapid screening environments.[7] Vocal analysis software is appealing because it provides a noncontact and inexpensive tool for rapid screening, requiring only a computer and microphone. However, most of the research on vocal analysis software focused on the older Vocal Stress Analysis (VSA) technology and not the current full vocal spectrum systems.

Investigations on modern full spectrum vocal analysis software found it unable to detect deception above chance levels.[8] However, all of this research examined the lie or truth classifications provided by the software interface and did not "look under the hood" at the underlying vocal measurements provided by the system and examine their validity and classification potential.

STATE THE POTENTIAL SOLUTION AND RESEARCH METHODOLOGY

This research investigates the validity and deception and emotion detection ability of commercial vocal analysis software using experimental methods. A series of experiments were conducted requiring participants to lie, commit a mock crime, and experience cognitive dissonance and stress. Participant's voices from each experiment were recorded and submitted to modern vocal analysis software for processing[9]. In addition to the classification provided by the software, the raw vocal variables were extracted from the software and analyzed using statistical and machine learning methods.

Replicating earlier research the vocal analysis software's built-in deception classifier performed at the chance level. However, when the vocal variables were analyzed independent of the software's interface, the variables documented to measure Stress, Cognitive Effort, and Fear significantly differentiated between truth, deception, stressful, and cognitive dissonance induced speech.

The results of a factor analysis suggest the existence of stable latent variables measuring Conflicting Thoughts, Thinking, Emotional Cognitive Effort, and Emotional Fear. A logistic regression model using the vocal measurements for predicting deception outperformed machine learning classification approaches (Support Vector Machine and Decision Tree) with a prediction accuracy ranging from 46 percent to 62 percent.

Despite the discouraging performance of commercial vocal analysis software's built-in classification, the variables underlying these classifications hold promise for predicting emotion and deception if properly calibrated to specific screening or security environments.

STATE THE END USERS/CUSTOMERS/ WHO WOULD BENEFIT

Since 9/11, the US Department of Homeland Security (DHS) has been seeking to increase the country's technological capability to secure its borders and airports. In response to this need a growing community of commercial security technology companies have emerged to service this niche industry. According to CBP officials, many of these vendors are "selling solutions in search of a problem." They may offer "one-size-fits-all technologies" with exciting feature lists. However, these systems depend on specific operating characteristics (e.g., polygraph style, rapid screening) and rely on single modalities (e.g., the voice).

This research investigates the potential of vocal analysis software to assist DHS in securing our borders and airports from threats.

STATE THE CHALLENGES TO ATTAINING THE SOLUTION AND RESULTS

The vocal analysis software vendors refute contradictory findings by arguing the built-in algorithms only work in the real world where tension, stress, and consequences are high. Creating these possibly harmful situations for experimental participants is not feasible. To overcome this limitation, careful experimental design based on communication and social psychology theory must be implemented to evoke emotions that occur during high stakes lies, without creating actual peril or harm.

If strong statistical relationships between vocal analysis software variables and emotions are replicated, we must try and interpret a black box system. The variables are calculated using propriety algorithms and are not standard. Research must occur in tandem corresponding these findings with standard phonetic measurements (e.g., fo, intensity, pitch contours) to better understand the emotional vocal behavior. This will further our scientific understanding and allow us to better calibrate vocal technology for specific security screening contexts.

We must be careful not to over rely on any one cue, vocal or otherwise. People and deceitful or truthful do not all behave the same. Some people may leak cues in their voice while others do not. Any technology solution implemented to observe and detect people should include multiple sensors. For the person that controls their voice well, their pupils, heart rate, or linguistic content will betray their hostile intent.

CONCLUSION

This research examines how reliable and valid commercial vocal analysis software is for predicting emotion and deception in security screening contexts using experimental methods. While research exists that evaluates current vocal analysis software's built-in classifications, there is gap in our understanding on how it may actually perform in a real high stakes environment.

Our voices are encoded with emotional information. While it is complex and difficult to develop software to classify emotion from the voice, it is possible. This research examines the variables produced by commercial vocal analysis software for predictive potential and statistical validity in identifying emotion and deception. It is unrealistic to rely completely on the voice to detect deception and hostile intent for all people and all situations. But, by exploring the vocal variables used by the software, we are able to correspond and fuse them with other detection technologies for higher prediction reliability and accuracy.

Implementing an unreliable and invalid detection technology could place the country's security in jeopardy by failing to detect actual threats. Just as deleterious, however, would be to dismiss technology, such as vocal analysis, before it has been thoroughly examined. This would deprive DHS of a valuable tool for detecting threats and securing our homeland.

ABOUT THE LEAD AUTHOR

Aaron C. Elkins *is a postdoctoral researcher at the National Center for Border Security and Immigration (BORDERS), a DHS Center of Excellence at the University of Arizona. Aaron investigates how the voice and language reveal emotion, deception, and cognition for advanced human-computer interaction (HCI) and artificial intelligence applications. One application Aaron actively researches and develops technology for is automated interviewing and credibility assessment systems for rapid screening environments. These systems incorporate multiple behavioral and physiological sensors that inform an intelligent embodied conversational agent (AVATAR) interviewer. Complementary to the development of advanced artificial intelligence systems for security screening, is their impact on the people using them to make decisions. Aaron also investigates how human screeners are psychologically affected by, use, perceive, and incorporate the next generation of screening technologies into their decision making. He may be contacted at aelkins@cmi.arizona.edu.*

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Vibration Based Damage Detections of Scour in Coastal Bridges

Adel H. Elsaid and Rudolf Seracino

ABSTRACT

The ability to ensure the resiliency and to predict the future performance of coastal bridges is very dependent on identifying damages in critical components of the bridge rapidly after an event. Traditional vibration based damage detection efforts focused mainly on the detection of fatigue cracking. Although detecting fatigue cracking is important, it does not contribute significantly to the total number of bridge failures in the United States. A critical review of the up-to-date literature showed that hydraulic loading, including scour, is responsible for about 50% of the failed bridges. To this end, the primary focus of this project is the development and evaluation of damage features capable of rapidly identifying and quantifying the extent of deterioration of critical coastal bridge structures due to scour at submerged piers following extreme storm events. This paper illustrates the use of the curvature of horizontal mode shapes and introduces the "Modified Curvature Damage Factor."

INTRODUCTION

In its latest report, the National Bridge Inventory revealed that 603,168 bridges currently exist in the United States.[1] The Federal Highway Administration (FHWA) rated 25 percent of these bridges as "deficient." The American Association of State Highway and Transportation Officials (AASHTO) announced in their 2009 Bottom Line Report that 50 percent of US bridges are more than forty years old without sufficient information on their current condition.[2] And although these represent 50 percent of the bridges, they are responsible for 80 percent of structural deficiencies and about 75 percent of total deficiencies.

Wardhana and Hadipriono collected 503 cases of bridge failures that occurred from 1989 to 2000 in the United States. They concluded that the dominant types of failed bridges are steel beam/girder and steel truss bridges, which represent 50 percent of the total bridge failures. The next significant cases involve failures of concrete beam/girder and concrete slab bridges, representing 11 percent. It should be highlighted that the leading cause of bridge failures are flood/ scour (48 percent).[3]

Further, the visual inspection of bridges regulated by the FHWA has limited capabilities in detecting all possible damages in bridges and there is the potential to miss damage that appears between inspection intervals. Based on the current condition of bridges, the need for global damage detection methods that can be applied to complex structures has led to the development of methods that examine changes in the vibration characteristics of the structure.

DISCUSSION

The primary objective of this research is to develop and evaluate a rapid vibration-based damage detection (VBDD) technique capable of evaluating the condition of a bridge following an extreme hydro-meteorological event. This technique relies on the effect of scour at submerged piers on the response of the bridge superstructure without any underwater instrumentation.

RESEARCH SIGNIFICANCE

Extreme natural hazards, particularly hydro-meteorological disasters, are emerging as a cause of major concern in coastal regions. From a structural point of view, hydraulic loading due to flood and scour is responsible for about 50 percent of the failed bridges in the United States.[4] Scour failures tend to occur suddenly and without prior warning or signs of distress to the structure. The nature of the failure may lead to collapse of the bridge. During floods, the flowing water tends to excavate pits in front of the submerged bridge piers. As the velocity of floodwater decreases, the suspended sediments precipitate and fill the excavated pits. Consequently, following inspections and measures cannot furnish indications on the maximum depth reached by erosion during flood.[5] Moreover, the suspended sediments that fill the excavated pits do not provide good confinement for the pile since they are not as compacted as the rest of the soil. Therefore, rapidly assessing the condition of bridges after an event will inform the decision making process in the context of assessing evacuation and first responders' routes. It should be mentioned that, after meeting with NCDOT Division 3 maintenance engineers, the most reliable way to measure the level of scour is by underwater investigation using divers. Further, underwater investigations are performed once every four years, or when a bridge is overtopped.

RESEARCH METHODOLOGY

VBDD techniques have shown success in detecting several types of damage, such as fatigue cracking in steel beams. Since the primary objective of this research is to develop a damage detection framework capable of rapidly detecting critical damage of the superstructure as well as scour, VBDD techniques were selected to study their sensitivity for detecting scour. For this investigation, an idealized structure representing a two-span continuous bridge was selected. A schematic of the idealized structure is shown in Figure 1. This steel grid was investigated previously by Catbas and others to study the potential of two different damage-sensitive features for damage detection.[6] A finite element (FE) model was created and verified by the experimental results of Catbas, et al. After verification of the modal analysis, the model was modified to simulate an idealized coastal bridge, where the intermediate piles were modeled. The abutments at each end were idealized with simple pin and roller supports. Six FE models were created. The first model represented the reference case and the other five models simulated five different levels of scour. Scour was modeled as an increase in the unsupported height of the intermediate piles.

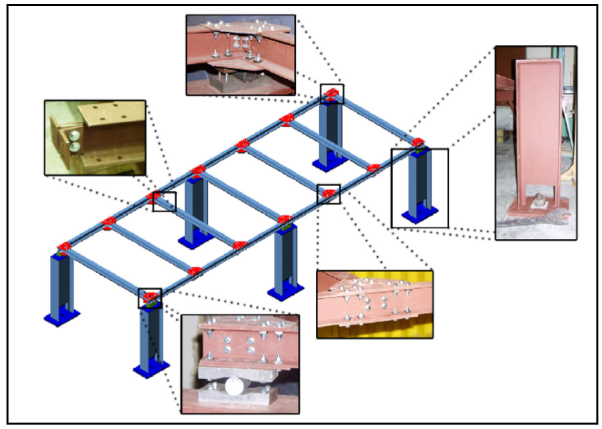


Figure 1. Schematic of the Test Specimen[7]

The results of the modal analysis were categorized according to (1) the vertically displaced mode shapes and (2) the horizontally displaced mode shapes. The dynamic characteristics of the vertically displaced mode shapes were insensitive to scour. This set of dynamic characteristics could be used to assess damages in the superstructure as investigated by previous researchers. Conversely, the dynamic characteristics of the horizontally displaced mode shapes showed significant changes due to scour. From the natural frequencies of the horizontally displaced mode shapes, it could be concluded that as the pile height increases, the natural frequency decreases. This is attributed to the decrease in the flexural stiffness of the intermediate support and leads to the hypothesis that the natural frequencies may be used to quantify the level of scour.

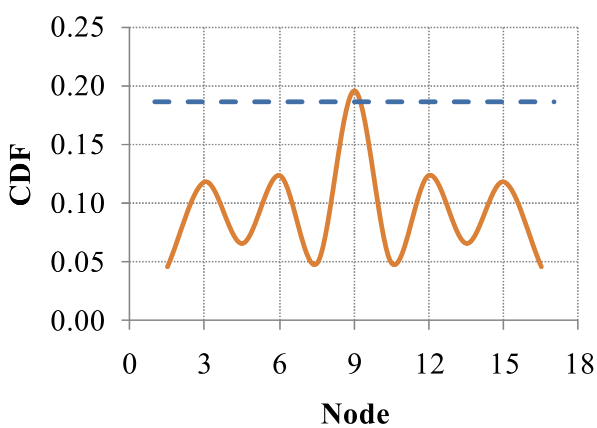
By calculating the change in the curvature of the horizontally displaced mode shapes, the location of damage at the intermediate pile was detected. To summarize the change in the curvature for a group of mode shapes, Abdelwahab and De Roeck introduced the Curvature Damage Factor (CDF) as

$$CDF = \frac{1}{N}\sum_{i=1}^{N}\left|\nu''_{oi} - \nu''_{di}\right| \quad (1)$$

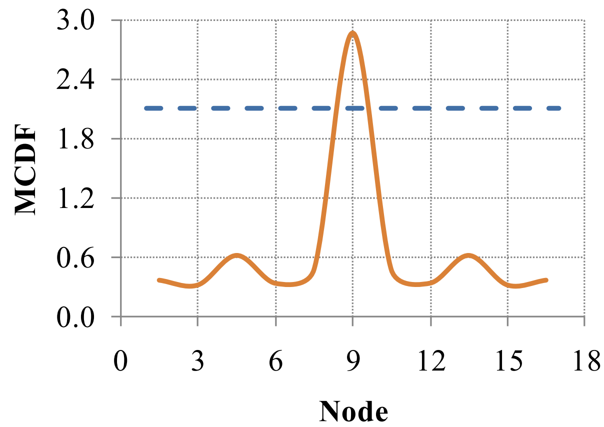
where N is the total number of modes to be considered, ν_o'' is the curvature mode shape of the reference structure and ν_d'' is that of the damaged structure.[8] By calculating the CDF for the first five horizontally displaced mode shapes, the location of damage at the intermediate support was captured. However, as shown in Figure 2a, the CDF also identified four potential false positives. This may be attributed to the high order mode shapes that do not contribute in the damage identification. A threshold is typically used, based on a statistical analysis of the CDF values, to discriminate between the true locations of damage and false positives, as given by the horizontal lines in Figure 2. To normalize the effect of the higher order mode shapes, a Modified Curvature Damage Factor (MCDF) was introduced as follows

$$MCDF = \frac{1}{N}\sum_{i=1}^{N}\left|\frac{\nu''_{oi}-\nu''_{di}}{\nu''_{oi}}\right| \quad (2)$$

where the MCDF calculates the average of the absolute ratio of the curvature change for a certain number of mode shapes. From Figure 2b, the MCDF clearly identified the location of scour.



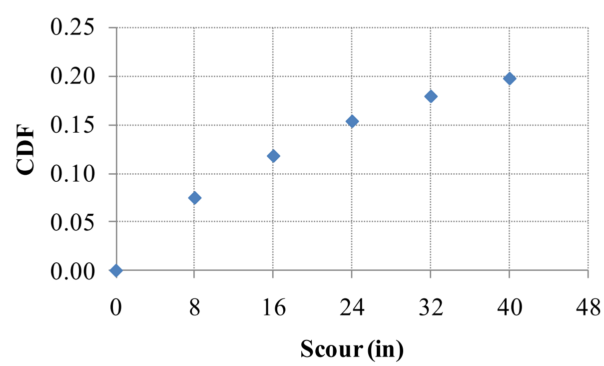
(a)



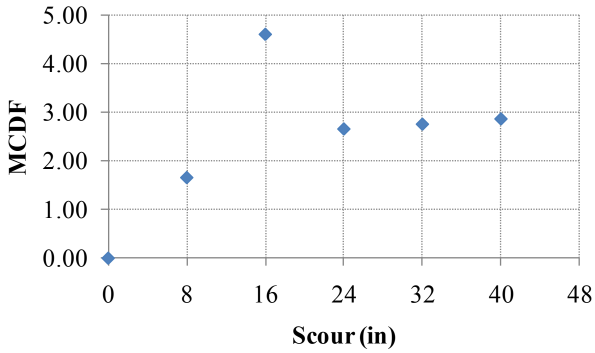
(b)

Figure 2. (a) CDF and (b) MCDF for the Idealized Structure at 40 inches of Scour.

By calculating the CDF and MCDF for the first five horizontally displaced mode shapes it was observed that the CDF and MCDF decreases as the scour level increases as shown in Figure 3. Therefore, the CDF and MCDF may be used not only to locate scour but also to quantify the amount of scour, which would be required to quantify the remaining strength or endurance of the scour damaged structure.



(a)



(b)

Figure 3. (a) CDF and (b) MCDF Calculated at Different Scour Levels

BENEFITS OF THE RESEARCH PRODUCTS

The end users of the technologies that will ultimately result from this research project will be technical in nature such as local/state bridge engineers or engineering consultants. It is anticipated that once the outcomes of this research project are successfully demonstrated in field applications that "plug-and-play black box" instrumentation packages will be developed and manufactured by others for this application. These kits would automatically collect and manipulate the raw data so that the prediction of the remaining strength or endurance is possible. The output of which will be used to inform agencies such as the Federal Emergency Management Agency (FEMA) to make informal decisions regarding relief efforts. Further, the developed framework can serve as a template for other critical infrastructure enhancing the resilience of communities.

ONGOING RESEARCH TASKS

The main difference between the investigated idealized structure and a real bridge is the presence of a concrete deck. To study the effect of the stiffness of the concrete deck on the horizontally displaced mode shapes for the detection of scour, a FE model for the Chicken Road Bridge in Lumberton, NC, was created. The FE model was verified by experimental work performed by previous researchers.[9] After verification, three more FE models were created to simulate three different levels of scour. The differences in mode shape curvatures were calculated for the horizontally displaced mode shapes. It should be mentioned that the FE results showed the same conclusions as the idealized structure models.

Having verified the proposed technique numerically, on-going efforts are dedicated to laboratory testing of an idealized structure (similar to that shown in Figure 1) and preparations for long-term field applications in collaboration with NCDOT Division 3 engineers. These tests will be used to evaluate the robustness of the technique allowing for the complexities, such as environmental conditions, not easily accounted for in numerical simulations.

CONCLUSION

Based on the findings of the current study, the following conclusions may be drawn:

1. Hydraulic loading due to flood and scour is the main cause of bridge failure in the United States.
2. Underwater assessment of scour after flood is of little significance, particularly in the context of assessing the remaining strength or endurance of the structure. This may be attributed to the precipitation of the suspended sediments in the scour pits.
3. The dynamic characteristics of coastal bridges can be divided into two categories: (1) vertically displaced mode shapes; and (2) horizontally displaced mode shapes.
4. The curvature of the horizontally displaced mode shapes is sensitive to scour, which to the best of authors' knowledge has not been considered in such an application before.
5. The "Modified Curvature Damage Factor" is proposed as a damage indicator with the potential to also quantify the extent of scour necessary to quantify the remaining strength.

ABOUT THE LEAD AUTHOR

Adel H. Elsaid *is a PhD student working as a research assistant in the Department of Civil, Construction, and Environmental Engineering at North Carolina State University (NCSU). He received his bachelor (2003) and master (2007) degrees in structural engineering from Ain Shams University, Cairo, Egypt. He worked as a professional structural engineer in a consulting firm from 2003 to 2008 until he joined NCSU to pursue his PhD degree. He has published one journal paper and two conference papers.*

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Decision Learning Algorithm for Acoustic Vessel Classification

Talmor Meir, Mikhail Tsionskiy, Dr. Alexander Sutin, Dr. Hady Salloum

ABSTRACT

Detection, tracking and classifying vessels of all sizes approaching ports and harbors is an imperative aspect to the security of complex maritime systems. This case study is an application of the passive acoustic method for vessel classification. The analysis of noise radiated by passing boats in Hudson River provides sound signatures and specific acoustic features of various boats. The features are then implemented into a decision-making algorithm used for final classification.

INTRODUCTION

Marine transportation plays a vital role in the global economic viability of the United States. As a maritime nation, the United States depends on a strong commercial maritime industry that is tied to maritime security and its stability. Ports and affiliated transportation are all part of a complex system and are potential targets, with wide-scale disaster implications. A need to detect, track and classify vessels of all sizes approaching our ports and harbors is imperative to the security of this country and its complex maritime systems. This case study is an application of the passive acoustic method for vessel classification. The complexity of the classification problem is approached using acoustic signature analysis. Prior studies at Stevens Institute of Technology found that reliable results can be obtained based on signal frequency analysis, specifically, some of the most useful signal characteristics are found in the signal's envelope spectrum. Detection of Envelope Modulation on Noise (DEMON) tool is used in this case study to analyze the acoustic signatures of various vessel types and to provide for specific features that are later implemented into a decision algorithm, which determines the final classification.

BACKGROUND

ACOUSTICS

Acoustics involves the study of the production, propagation, and reception of sound. As sound travels through water, the waves attenuate, which enable instrumentation to record the changes and associate them with vessel noise characteristics. The main sources of noise generated by a marine vessel are (1) mechanical noise of the main engine and auxiliary machine, (2) propeller cavitations noise, and (3) hydrodynamic noise of the moving vessel.[1] The acoustic signature produced by the radiating noise consists of a continuous broadband spectrum and line spectrum. It is the specific configuration of the narrow band frequencies that helps classify and identify different classes of vessels.

CLASSIFICATION ALGORITHMS-DECISION TREE

The classification objective is to identify vessels (ferry, speed boat, sail boat etc) based on a training set of acoustic signatures whose group-label is previously known and then be able to embrace any new observation. The general process of classification is placing individual vessels into groups labeled based on quantitative information of their attributes. Attributes are: an in-depth and structured set of categories that are usually denoted by a numerical code. In essence, the attributes are the preparation for the classification algorithm construction. A wide range of classification algorithms has been studied in various fields, some of which have been applied to acoustic signature classification. Common classification algorithms mentioned in acoustics studies are: neural networks, K-nearest neighbors, Gaussian, and decision tree. Due to its simplicity and ability to handle a mix type data set, the decision tree model was chosen as the classification algorithm for this case study. The decision tree uses relative entropy or Kullback-Leibler (KL) to study the contrast between two or more probability vectors. This approach sprung from information theory.[2] A typical decision tree encodes in a form of tree, where data passes through branch like nodes, constructed from the attributes-rule mentioned earlier and eventually flows through to the final leafs representing the group label (ferry, sail boat, speed boat etc). The node selection is accomplished by selecting the attribute that divides the inhomogeneous data into minimal inhomogeneous subsets using entropy calculations (Kullback-Leibler method).

METHODOLOGY

DATA COLLECTION

Stevens Passive Acoustic Detection System is composed of four ITC-6050C hydrophones manufactured by International Transducer Corporation and connected to an underwater computer, which communicates and feeds acoustical information (both acquisition and analysis) into the control room of the Maritime Security Laboratory (MSL) at Stevens Institute of Technology (figure 1a).

(a)

(b)

Figure 1. (a) picture of the system of the deck of RV Savitsky prepared for deployment and view of the test site (b) with hydrophone position shown by red circle.

This deployment of the acoustic system was initiated in part at the Summer Research Institute program of Stevens University, July 2010. The underwater computer and hydrophones were dropped into the Hudson River approximately 300 ft off the Hoboken NJ shore (Fig.1b.). The database collected during the summer of 2010 is composed of acoustical events of approximately 950 ships accompanied by pictures, video and a manual log record of environmental conditions.

DATA PROCESSING

The task of marine vessel tracking and signature extraction is achieved by using cross-correlation processing of acoustic signals that are detected off four underwater hydrophones. As the vessel noise radiates through the water, it reaches each hydrophone at a different time. The time delay between the hydrophones is the determining factor that allows the system to detect the direction of the moving vessel.

We applied DEMON (Detection of Envelope Modulation on Noise) analysis; for ship classification as it is one of the most reliable acoustic means for ship noise detection and classifications.[3] The noise radiated by a ship is modulated at a rate dictated by parameters of the propeller and engine (number of blades and rotational speed). Evaluation of that modulation helps provide information on the ship, such as the shaft rotation frequency, that can be used for ship classification. Stevens has developed software for measurements of the vessel modulation spectra. DEMON analysis construction involves the following algorithm:

1. Measured signal is divided into parts of 1/1000 of a second. In our case, since the signals were measured at 200 kSamples/sec these parts contain 200 measured points.
2. At each part, the measured samples are squared, mean value of the results is calculated, and then square root of the result is computed. Hence out of initial 200 points in each signal part we have received 1 point for further analysis.
3. Some predefined number (e.g. 2048) of these new calculated subsequent points is collected; their mean value is calculated and then subtracted from initial points. The results are analyzed using FFT Power Spectrum.
4. Steps 1-3 are repeated for the rest of the measured signals.

RESULTS

Examples of the recorded DEMON spectra for several boats are presented in Figures 2 and 3.

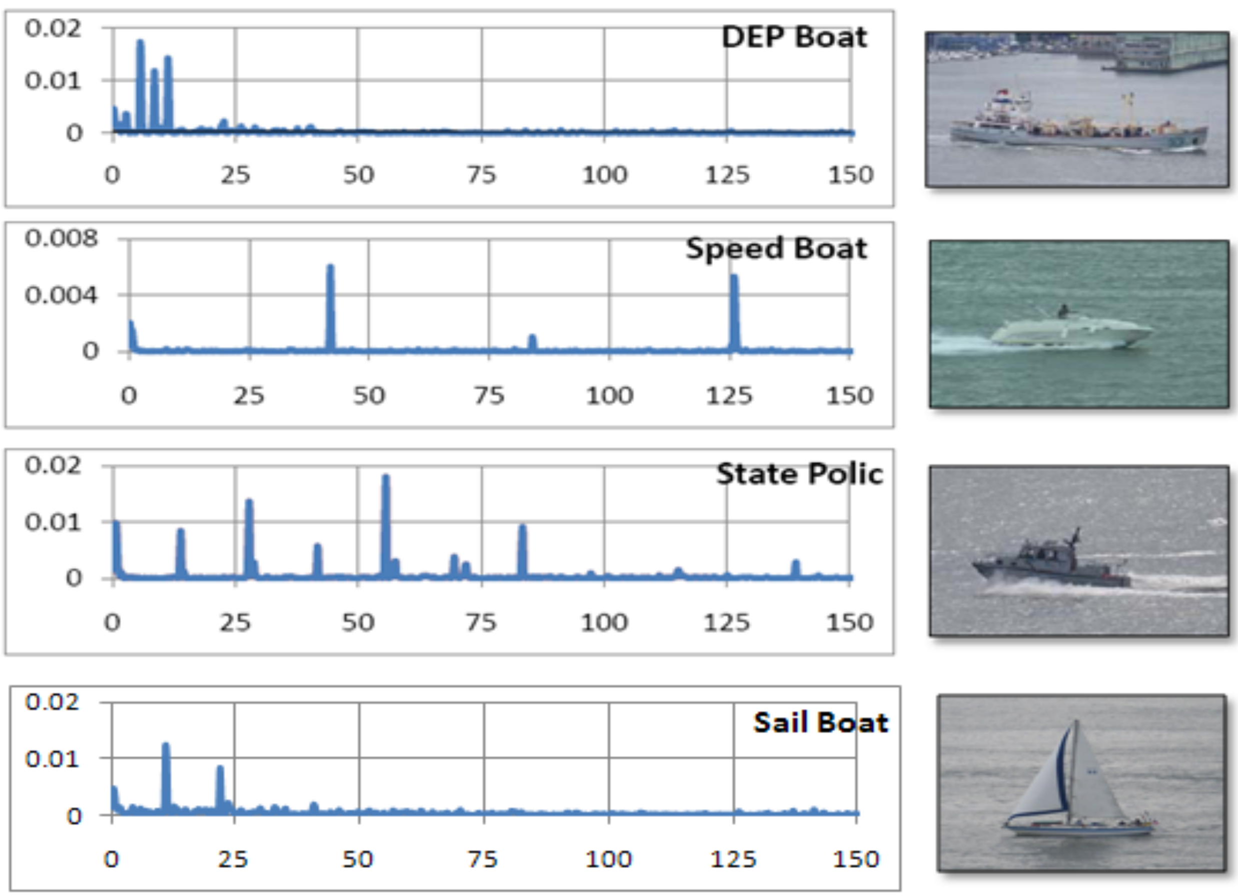


Figure 2. DEMON spectra of various vessels recorded in the Hudson River.

Based on the acoustic signature analysis, the following table provides the attributes and their associated splitting sub-populations that were significant dividers in the classification process:

Attributes	Attributes Subpopulations	Descriptions
Number of Peaks	2-3 peaks	The number of line spectrum that appear on each ocoustic signature
	4 peaks	
	other	
Main Frequency	10-14 Hz	The frequency of the most pronounced spectrum
	41-46 Hz	
	other	
Maximum Frequency	14-41 Hz	The range of the last peaked line spectrum
	Above 130 Hz	
	other	
Amplitude Ratio	2-3 peaks	Ratio of the main frequency versus the second most pronounced frequency
	other	

Table 1. Attributes description and subpopulation values

An example of the attributes extraction of Ferry A and Ferry B is shown in Figure 3 and their attributes values are shown in the Table 2. These observation models allow the classification algorithm to separate and therefore identify the ferries from each other and from all other vessels in the water.

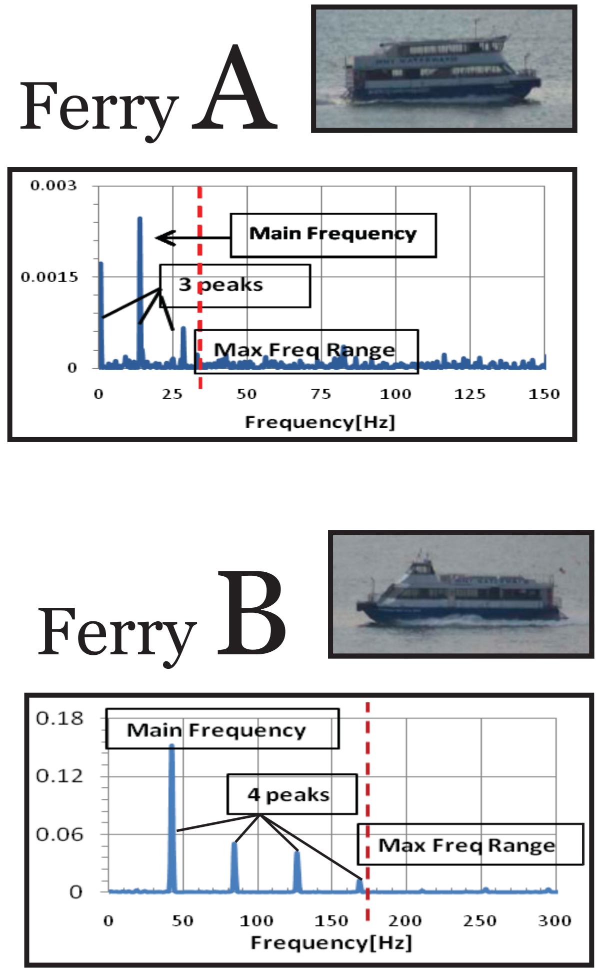
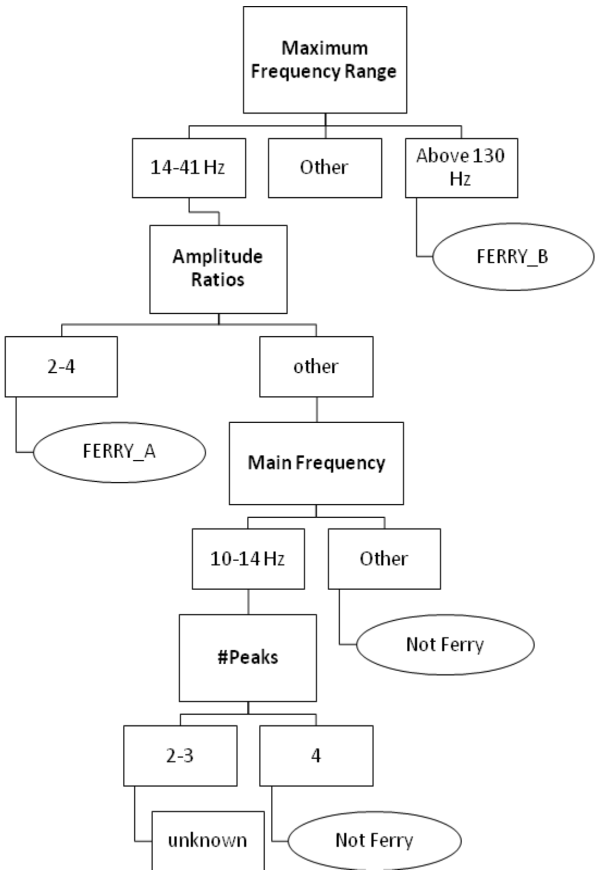


Figure 3. Illustration of the selection diagram for two types of ferries.

Type	# of peaks	Main Freq	Max Freq range	Amplitude ratio
Ferry A	3	~11 Hz	20-40 Hz	2<x<4
Ferry B	4	~ 41 Hz	<130 Hz	2<x<4

Table 2. Attributes values for Ferry A and Ferry B

The following decision tree was constructed from the DEMON signatures of twenty recorded boat sounds based on the calculation of the degree of homogeneousness of the three group labels Ferry A, Ferry B, and Not ferry.



CONCLUSION

This case study has demonstrated the effectiveness of utilizing DEMON acoustic signatures for boat identification. Attributes for classification were extracted from the boat signatures and the simplified decision tree was built. Future work is needed in maintaining a catalog for acoustic signatures; developing a library of few hundred boat signatures will allow for more accurate classification of vessels.

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Optimal Defensive Allocations in the Face of Uncertain Terrorist Preferences, with an Emphasis on Transportation

Chen Wang and Vicki M. Bier

ABSTRACT

This paper extends a game-theoretic model for identifying optimal defensive resource allocations to the case of realistic multi-attribute terrorist objective functions. In particular, we compare the optimal defensive resource allocations to ten major US urban areas in the face of uncertain terrorist preferences with and without transportation-related attributes. The defender's uncertainty about terrorist preferences is addressed both by probability distributions over the attacker's attribute weights, and by allowing for attributes that are important to the attacker but not known to the defender. Estimates of the various terrorist attribute weights are inferred from (partial) ordinal expert judgments using the technique of probabilistic inversion.

INTRODUCTION

Allocating a limited budget to protect potential targets against terrorist attackers is an important but difficult task. In doing so, we must take into account both the strategic nature of the attackers, and also the defender's uncertain knowledge about attacker preferences. A variety of game-theoretic models in the face of defender uncertainty have been studied and applied. [1]

This study is based on the sequential game with incomplete information developed by Bier et al. [2] In that model, the defender moves first to allocate her defensive resources among the potential targets under uncertain knowledge about attacker preferences; the attacker then selects the target with the highest payoff to attack, in light of any defensive investments.[3] Knowing or assuming that the attacker would play his best response to any given defensive allocation, the defender wishes to choose her allocation so as to effectively protect against attacks, deter attacks, or deflect attacks to less important targets. However, with uncertainty about the attacker's utility function, the defender cannot predict the attacker's best response for sure; therefore, the defender is assumed to minimize her expected total loss (where the defender objectives may in general be different from the attacker objectives).

This paper extends the above game-theoretic model for determining optimal defensive resource allocations to the case of more realistic multi-attribute terrorist objective functions. In particular, we compare the optimal defensive resource allocations in the face of uncertain terrorist preferences with and without transportation-related attributes. The defender's uncertainty about terrorist preferences is represented both by probability distributions over the attacker's attribute weights, and by allowing for attributes that are important to the attacker but not known to the defender.

One closely related task is to elicit the attacker attribute weights in the terrorist multi-attribute objective from the judgments of intelligence experts. However, direct estimation of attribute weights can be difficult, since intelligence analysts are usually not familiar with utility theory, and historical data about terrorist attacks are relatively sparse. In such cases, indirect elicitation may be preferable. In particular, this paper uses an approach in which experts are asked to give (partial) rank orderings of attack strategies or targets, and the attribute weights in the attacker objective function are then inferred from those partial rankings using probabilistic inversion.[4] We believe that this approach will increase the acceptance of quantitative methods by intelligence experts, and also make it possible to elicit the opinions of a large number of experts in an automated (e.g., online) manner.

MODEL

As in Wang and Bier,[5] we assume that the defender's objective is to minimize the total expected loss, as given by

$$\min_{c_1,\dots,c_n} \sum_{i=1}^{n} h_i(c_1,\dots,c_n)p(c_i)v_i \qquad \textit{such that} \sum_{i=1}^{n} c_i \le B$$

where:

- n = number of targets
- c_i= defender's resource allocation to target i
- B = defender's total budget
- v_i = defender's valuation of target i
- $h_i(c_1,\dots,c_n)$ = probability of an attack on target i
- $p(c_i) = e^{-\lambda c_i}$ = = success probability of an attack on target i, as a function of the budget allocated to target i, where λ is the cost effectiveness of defensive investment.[6]

The attacker is then assumed to observe the defender's resource allocations c_i and then choose the target with the highest payoff in light of any defensive investment:

$$\max_i \; p(ci)Ui$$

where:

- $U_i = \sum_{j=1}^{m-1} x_j \quad u_j(A_{ij})x_j + e_i x_m$ = attacker's utility of target i
- x_j= attacker weight on attribute $j(x_j \ge 0, j{=}1, \dots, m,$ and $\sum_{j=1}^{m} x_j = 1)$
- A_{ij} = attacker rating of target i on attribute $j(j{=}1, \dots, m-1)$
- u_j= single-attribute utility function for attribute , taking on values in [0, 1].
- ε_i = attacker utility of target i on the unobserved attribute (modeled as independent, identically uniformly distributed random variables taking on values in [0, 1]).

Experts are asked to give partial rank orderings of the various possible attacker targets or strategies (e.g., the top five and bottom five). The probability distributions of the various attribute weights are then estimated using probabilistic inversion.[7]

CASE STUDY

We conduct a case study on the ten major US urban areas with the highest expected damage from terrorism,[8] based on two different sets of attributes: "macro" attributes (expected property losses from terrorism, and total population);[9] and transportation-related attributes (yearly air departures, and average daily bridge traffic on the most heavily traveled bridge).[10] The ten urban areas are: New York City (NYC); Chicago; San Francisco; Washington, DC; Los Angeles (LA); Philadelphia; Boston; Houston; Newark; and Seattle. The attribute values for these ten urban areas are presented in Table 1.

Urban Area	Expected Property Loss from Terrorism ($ million)	Population	Yearly Air Departures	Average Daily Bridge Traffic
NYC	413	9,314,235	23,599	596,400
Chicago	115	8,272,768	39,949	318,800
San Francisco	57	1,731,183	19,142	277,700
Washington, DC	36	4,923,153	17,253	254,975
LA	34	9,519,338	28,816	336,000
Philadelphia	21	5,100,931	13,640	192,204
Boston	18	3,406,829	11,625	669,000
Houston	11	4,177,646	20,979	308,060
Newark	7.3	2,032,989	12,827	518,100
Seattle	6.7	2,414,616	13,578	212,000

Table 1. Attribute values for the ten urban areas with the highest expected terrorism losses.

We consider two hypothetical experts who give partial rank orderings of these urban areas. In particular, Expert 1 ranks NYC, Chicago, LA, San Francisco, and DC as the top five most attractive cities (in that order), and Houston at the bottom; Expert 2 ranks Chicago, LA, NYC, Houston, and Boston as the top five cities (in that order), and Philadelphia at the bottom.

For this case study, we assume that the attacker's single-attribute utility function for attribute $j (j = 1, \ldots, m - 1)$, $u_j(A_{kj})$ is proportional to $\ln(\frac{A_{kj}}{a_j})$ (where $a_j = \min_i A_{ij}$), and hence measures how much more attractive target k is than the least desirable target on attribute j. They are normalized so that $u_j(A_{kj}) = 1$ when target k is the most attractive target on attribute j. This choice of utility function is also consistent with Fechner's law, which states that human perceptions are typically logarithmic in the magnitude of the original stimuli.[11] For example, if the expected property loss in Chicago is doubled from 115 to 230 million dollars, the attacker's single-attribute utility increases by an additive increment proportional to ln(2).

The histograms in Figure 1 show the probability distributions for the attacker attribute weights inferred from the rankings of expert 1, with and without transportation-related attributes. Including transportation-related attributes reduces the expected weight on the unobserved attribute from 31 percent to 24 percent. However, the weight on the unobserved attribute is still substantial, reflecting the fact that the rankings given by Expert 1 do not place a lot of importance on air departures and bridge traffic.

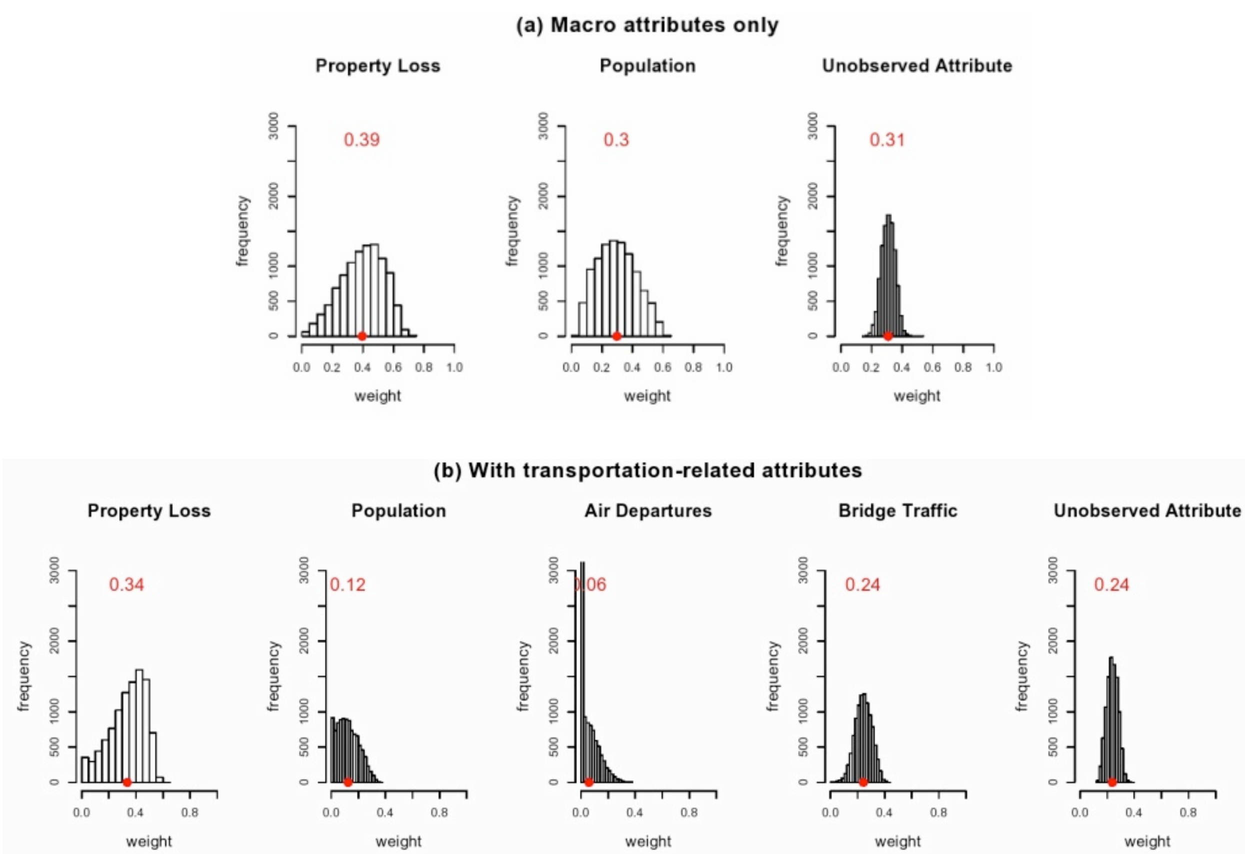

Figure 1. Attribute weights inferred from the rankings of Expert 1.

The optimal defensive resource allocations based on the elicited attribute weights from Expert 1 are shown in Figure 2. Note that San Francisco is rated higher than DC both by Expert 1, and on the defender objective function (property loss). However, as shown in Figure 2a, when using only the two macro attributes, DC gets more resources than San Francisco, reflecting the fact that the model does not have enough information to distinguish clearly between San Francisco and DC. Including the transportation-related attributes allows the model to perform better in this regard, as shown by the reversed ranking of San Francisco and DC in Figure 2b.

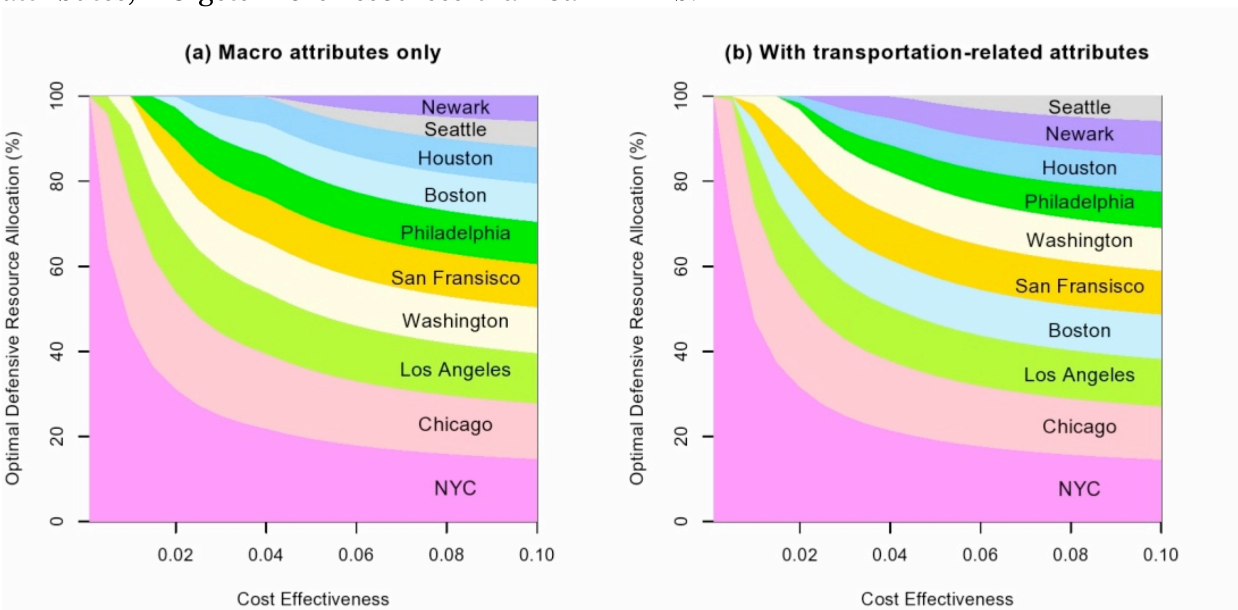

Figure 2. Optimal defensive allocations based on elicited attribute weights from Expert 1.

Figures 3 and 4 give comparable results for hypothetical Expert 2. Figure 3a shows that without transportation-related attributes, the model puts 40 percent of the weight on the unobserved attribute, indicating that the macro attributes are not sufficient to adequately represent the beliefs of Expert 2. By contrast, Figure 3b shows that the ratings given by Expert 2 are consistent with a high weight on transportation-related attributes. As a result, the weight on the unobserved attribute drops to only 18 percent.

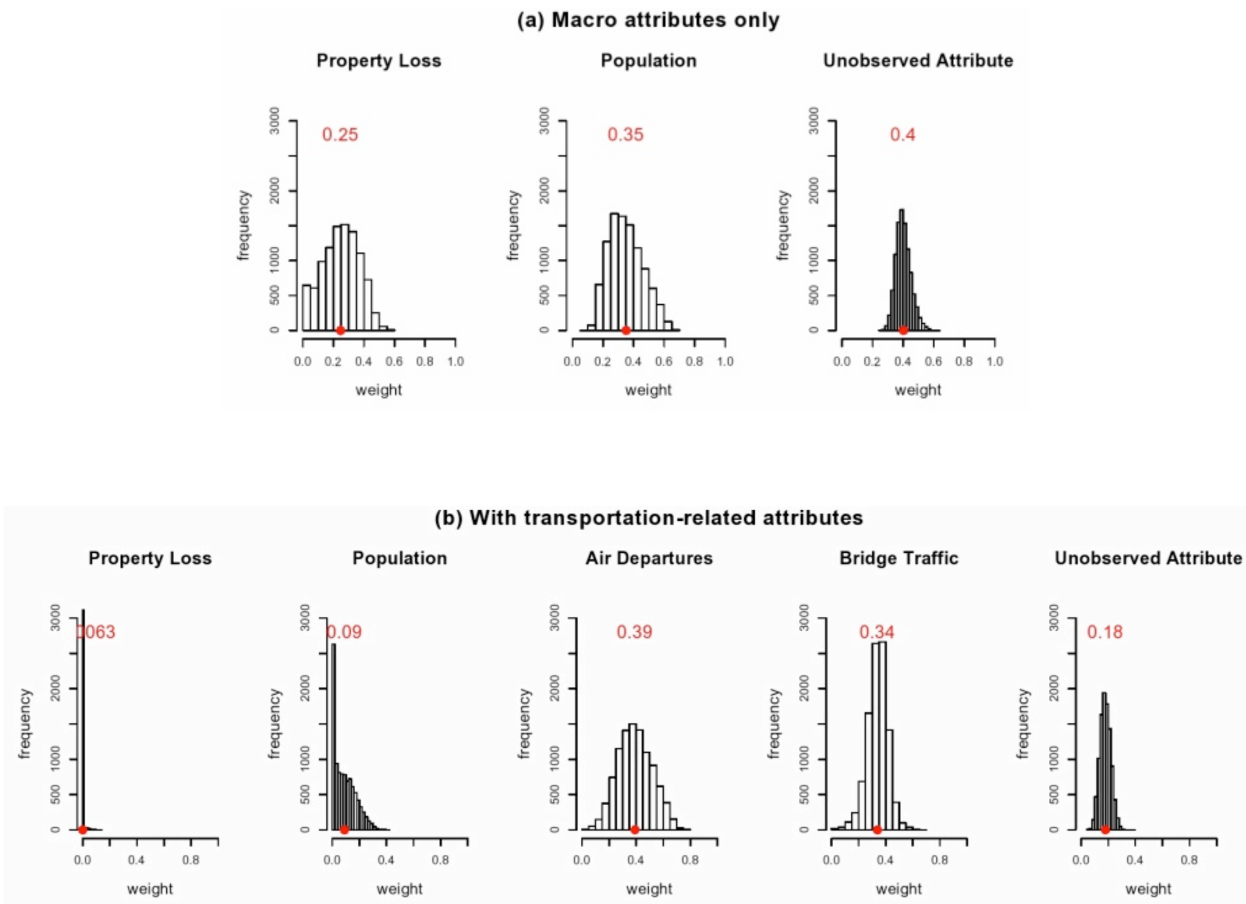

Figure 3. Attribute weights inferred from the rankings of Expert 2.

Using only macro attributes also performs poorly for the optimal defensive allocations resulting from the judgments of Expert 2, since the expert's target rankings (Chicago, LA, NYC, Houston, and Boston as the top five cities, and Philadelphia at the bottom) reflect high weights on transportation-related attributes. For example, Houston is ranked fourth in air departures, but receives only modest funding in Figure 4a; by contrast, Philadelphia is ranked seventh in air departures and tenth in bridge traffic, but receives relatively high levels of funding in Figure 4a, because of its large population. With the inclusion of transportation-related attributes, the model does a much better job of matching the stated rankings given by Expert 2, as shown in Figure 4b.

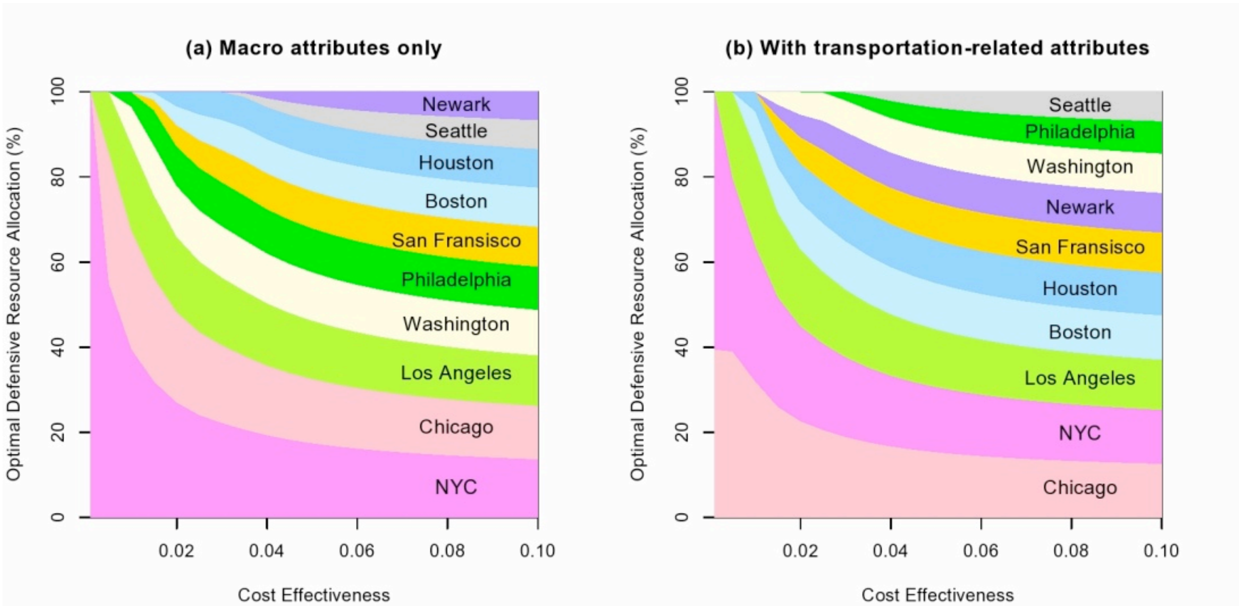

Figure 4. Optimal defensive allocations based on elicited attribute weights from Expert 2

CONCLUSION

Intelligence analysts are sometimes unable or unwilling to provide quantitative risk estimates.[12] This paper bridges this gap by providing a practical and methodologically credible way for risk analysts to obtain quantitative risk estimates from ordinal rankings provided by intelligence analysts. In particular, if experts find it difficult to estimate attacker attribute weights, indirect elicitation based on (partial) rank ordering of attack targets or strategies can help ease the elicitation burden. We believe that this approach will increase the acceptance of quantitative approaches by intelligence experts, and increase the number of experts whose opinions can be elicited in an automated (e.g., online) manner.

In addition, the inclusion of unobserved attributes makes it possible to use our model in a diagnostic manner, to indicate whether we have enough attributes. Finally, the results presented here (based on hypothetical expert judgments) show that including transportation-related attributes can help to distinguish between targets, especially when an expert believes that the attacker puts high weight on transportation-related attack strategies.

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Consequence Assessment for Complex Food Transportation Systems Facing Catastrophic Disruptions

Yu Zhang and Alan Erera

ABSTRACT

This white paper describes our research on vulnerability assessment for complex transportation system facing catastrophic disruptions. The proposed methods attempt to understand the consequences of disruptions to major freight transportation systems, where the consequences are measured here in the limited sense of increased supply chain costs. A case study applying the ideas to the US corn export supply chain is provided. The paper explains how the dataset for the corn network is constructed from public data sources and presents the results of an example assessment, focusing on a set of dams and locks on the Mississippi River System.

INTRODUCTION

The United States is one of the largest grain producers and top grain exporting countries in the world. For the three primary export field crops – corn, wheat and soybean – total exports in 2007 measured 110 million metric tons (mmt) with a total value of $13-17 billion.[1] On the basis of value alone, the revenue from grain exports is critical to the economic health of US grain producers and related industries.

Export flows for grains rely on three freight transport modes – truck, railroad and inland water – while moving through the mainland US en route to an export port. From the export port, the grains are shipped to destination countries by bulk ocean vessel, with the exception of exports to Mexico and Canada. In this paper, we focus on the domestic long-haul segment of the grain export transportation chain, i.e., the portion of transportation conducted by railroad and barge.

Currently, the US grain export supply chain faces large challenges due primarily to enormous freight volume and relatively tight transport capacity. Moreover, the supply chain is often affected by various disruptions, arising from natural hazards, some recent examples of which have been catastrophic. For example, Hurricane Katrina hit the Gulf of Mexico in 2005, resulting in a major disruption to grain transportation. Barge and rail traffic was slowed, because of serious damage to transportation facilities and displacement of employees.[2]

Our research aims to identify and determine how to understand the potentially severe supply chain cost risks present in complex transportation systems supporting US food supply chains, with the intent of enabling significant improvement in food supply chain security, preparedness and resiliency. Models are developed to assess the vulnerability of critical infrastructure and key resources (CI/KR) in the transportation system, where vulnerability in this case is measured by the potential for large supply chain cost increases given disruption. Understanding vulnerabilities in the system is important for the effective allocation of protection investment.

TECHNICAL DETAILS: MODEL AND DATA COLLECTION

CONSTRUCTION OF GRAIN EXPORT SUPPLY CHAIN NETWORK

The grain export supply chain is modeled as a network. Each node in the network represents a Business Economic Area (BEA) in the United States.[3] Transport routes between nodes, mainly railroads and inland waterways, are modeled as arcs. Critical infrastructure in the transportation system, such as locks and dams on rivers, are included in this set of arcs. The goal of the network model is to predict how grain flows will move between production sources and export ports, given the relative costs and capacities of the underlying transportation infrastructure. In this initial research, we assume that costs can be modeled as linear in total freight flow along arcs, but that arcs have limited capacity for flow. When arc capacities are reduced due to a disruption, such a model can be used to predict how freight will be move post-disruption, and provide a measure of potential supply chain cost impact. The resulting optimization problem is a Minimum Cost Flow (MCF) problem, which can be solved efficiently.[4] System behavior over time can be simulated by using a time-space network, an expansion of the static network over the time horizon. Figure 1 illustrates a sample network and its time-space version.[5]

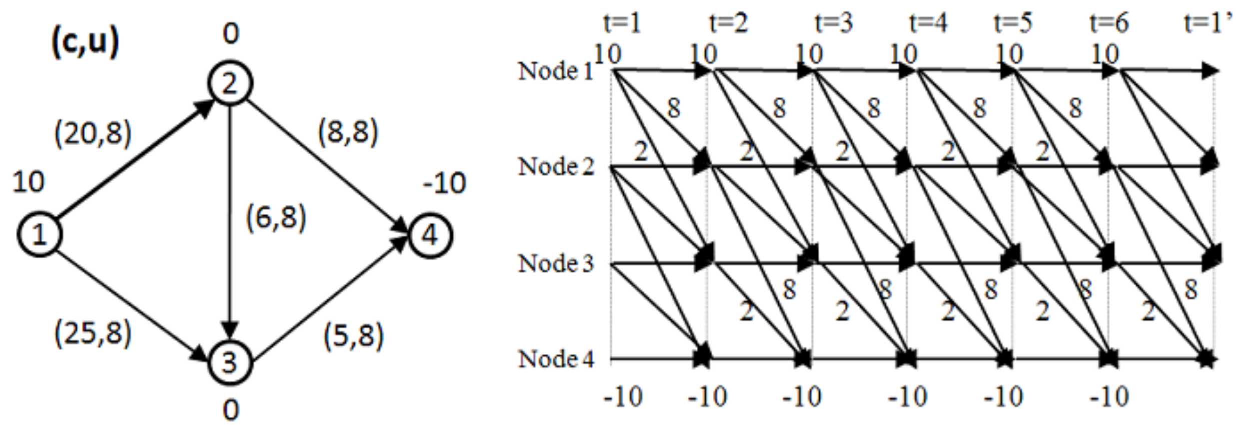


Figure 1. A Sample Network

DATA COLLECTION

Our vulnerability assessment methodology is applied to the US corn export supply chain. Figure 2 shows an overview of the transportation network for exporting corn. Corn is mainly grown in the "Corn Belt," the dark green region in this figure. The primary destinations of export flows within the US are the Gulf of Mexico and Pacific-northwest (PNW). Corn is shipped to New Orleans by barge and railroad and shipped to PNW by railroad. Barge is preferred if available because of its lower cost.

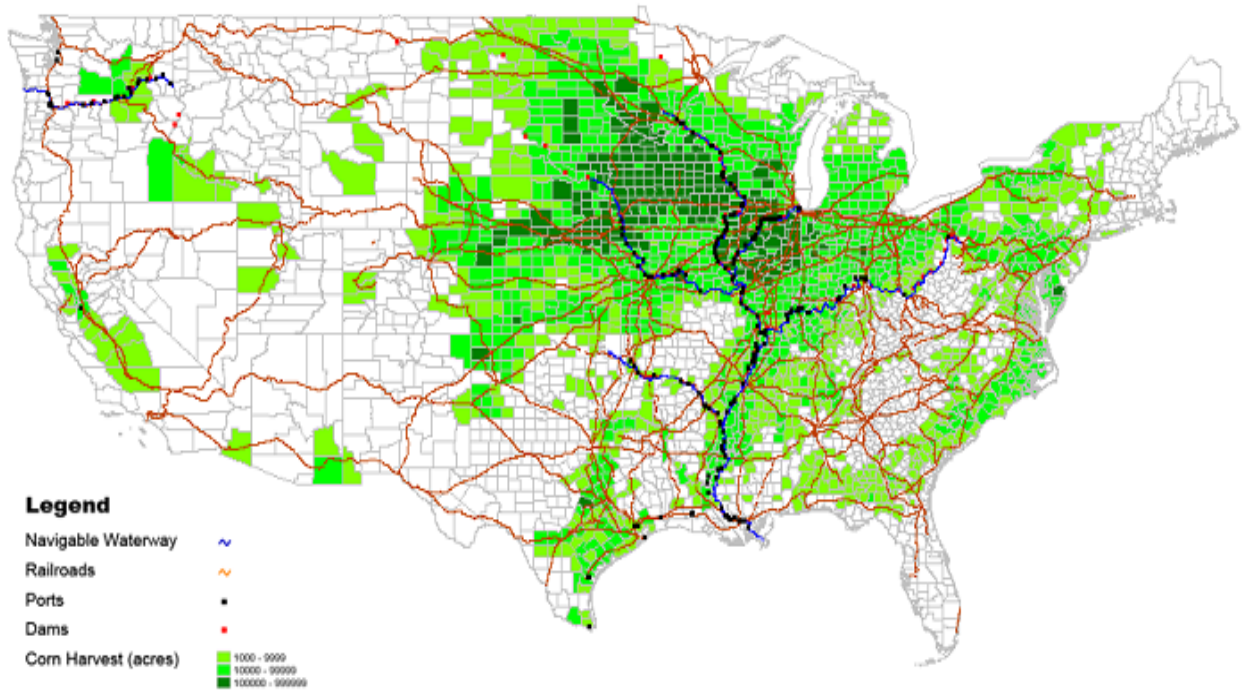
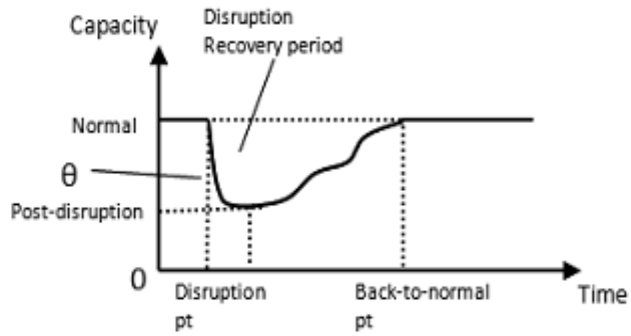


Figure 2. Map of Corn Export Supply Chain

All data for our example case study was collected from public sources, such as the US Department of Agriculture (USDA), The US Department of Transportation (USDOT), and the US Army Corps of Engineers (USACE). Technically, the data is collected separately for the two modes: inland water and railroad. In the inland water sub-network, each node represents a Business Economic Area (BEA) along the Mississippi River System.[6] Arcs connect two BEA along the rivers. Locks and dams limit the capacity of corresponding arcs. The inland water data was obtained primarily from the Grain Transportation Report (GTR).[7] In the railroad sub-network, each BEA is again represented by one node. Ninety-one BEA that have rail transportation activities related to corn export are involved, as determined from the Public Use Waybill (2007).[8] The two sub-networks are connected by arcs representing intermodal transportations between proper nodes. Supply and demand in the network are also determined from the GTR.[9]

MODELING DISRUPTIONS

A disruption can be modeled as reduction of arc capacity in the network. The general disruption-recovery process, illustrated in Figure 3, can also be modeled in time-space network. In this figure, the affected component is disrupted at the time "disruption point." As the magnitude of disruption increases, the capacity of the affected arc drops to minimum. Subsequently, the effect of disruption diminishes and the arc capacity recovers slowly to the normal state at the time "back-to-normal point".



$$\text{Min} \sum_{(i,j)\in E} c_{ij}x_{ij}$$

$$\text{s.t.} \sum_{j\in N} x_{ij} - \sum_{j\in N} x_{ji} = b_i, \forall i \in N$$

$$0 \le x_{ij} \le u_{ij} - \theta d_{ij}, \forall (i,j) \in E$$

Figure 3. General Recovery Process and MCF Model with Disruption

Figure 3 also provides a simple formulation of the mathematical optimization problem given a disruption. The notation used is standard MCF notation.[10] Additionally, θ represents the maximum magnitude of the disruption and reflects the relative effect that disruption exerts on arc (i,j).

The relationship between total supply chain cost and magnitude of disruption reflects the impact of disruption to the system. It is described by a so-called **Impact Curve**. We prove that the impact curve resulting from our model is a convex, piecewise linear, non-decreasing function of disruption magnitude, illustrated in Figure 4. Given the impact curves of all network components, their vulnerability can be compared. But the vulnerability of one component may not dominate that of another, as shown in the right part of Figure 4, where component 1 is more vulnerable to smaller disruptions, but component 2 becomes more vulnerable as the disruptions grow larger.

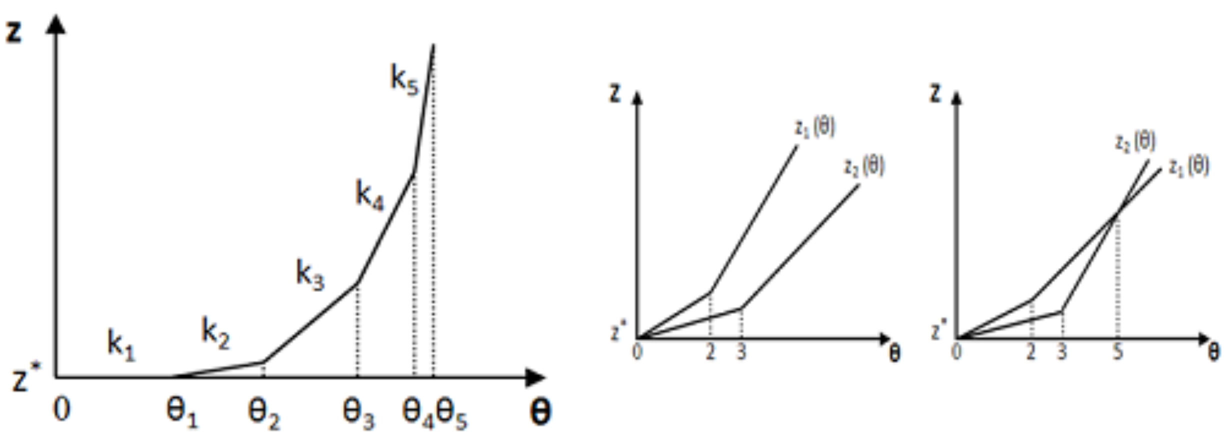


Figure 4. Impact Curves

VULNERABILITY ASSESSMENT ALGORITHM

An impact curve can be determined by a series of breakpoints and slopes between two breakpoints. Based on the observation, the **Dual Network Simplex Algorithm** is used to determine the impact curves for a selection of arcs in a network.[11] An outline of the procedure is as follows:

- Start from the optimal flow x of the nominal problem with no disrupted arcs;
- For each arc selected , do:
- If , then the assessment result is ; Go to the next arc;
- Set the arc flow and capacity to zero, resulting in excess and deficit at its tail i and head j;
- Perform dual pivots until excess/ deficit is zero or infeasibility is detected;
- Record pivot history, represented by

RESULTS OF VULNERABILITY ASSESSMENT

STATIC VULNERABILITY ASSESSMENT

The dams and locks on the Mississippi River System play a critical role in the corn export supply chain. Thus, we choose six representative dams and locks for assessment and number them from 1 to 6, hiding their actual names in this document. Since the static assessment model is developed using annual freight volume parameters and capacities, the impact curves represent a rough estimate of the annual impact to total supply chain cost due to a disruption. The impact curves are shown in the left graph of Figure 5. The right graph is the zoomed version.

In Figure 5, since the impact curves of Dams No. 5 and 4 are the steepest, the two locks are the most vulnerable. However, neither of the two dominates the other in vulnerability. By similar arguments, Dam No. 1 is the least vulnerable (except Dam No. 6). The vulnerability of Dam No. 1 is close to that of Dams No. 5 and 4. For Dams No. 2 and 3, the two curves intersect. Dam No. 3 is more vulnerable for small disruptions while Dam No. 2 is more vulnerable for large disruptions. Due to limited economic impact, Dam No. 6 is less vulnerable than the other targets, seen in the zoomed graph. As we can see, it is a little counter-intuitive that the dam on the downstream, which has more volume going through it, is not always more vulnerable.

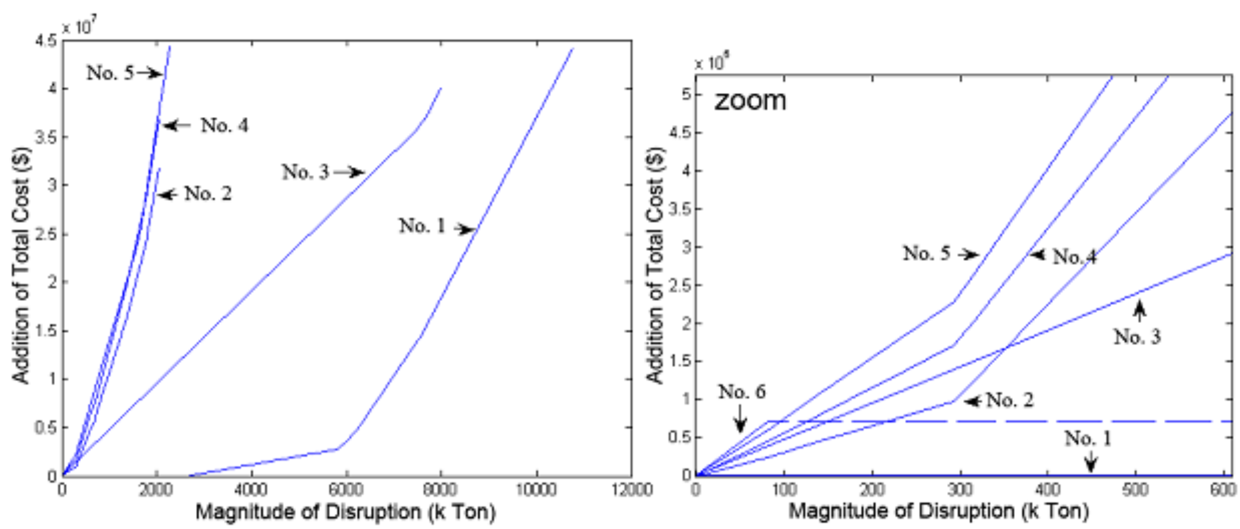


Figure 5. Static Vulnerability Assessment

DYNAMIC VULNERABILITY ASSESSMENT

The same selection of targets is used in dynamic assessment; however, each target corresponds to a set of transportation arcs originating at different time periods in the time-space network. The result is illustrated in Figure 6. The upper left graph shows the impact curves of all selected targets at all time periods; the upper right graph only shows the most vulnerable ones; the lower ones are the zoomed versions of the upper right graph.Besides identifying the most vulnerable targets, the dynamic assessment also provides the critical time for each target, i.e., the time at which the target is most vulnerable. Simply stated, Dam No. 5 is most vulnerable around week twenty-seven of the year, since the harvest peak in its vicinity is around week twenty-seven. Dam No. 4 is most vulnerable around week seventeen. Dam No. 2 is most vulnerable around week forty-five. Dam No. 1 does not appear in the list of most vulnerable targets because it has redundant capacity that can absorb small disruptions. Dam No. 3 does not appear in the list, since there is a railroad hub nearby and there are good alternative routes available when the dam is disrupted.

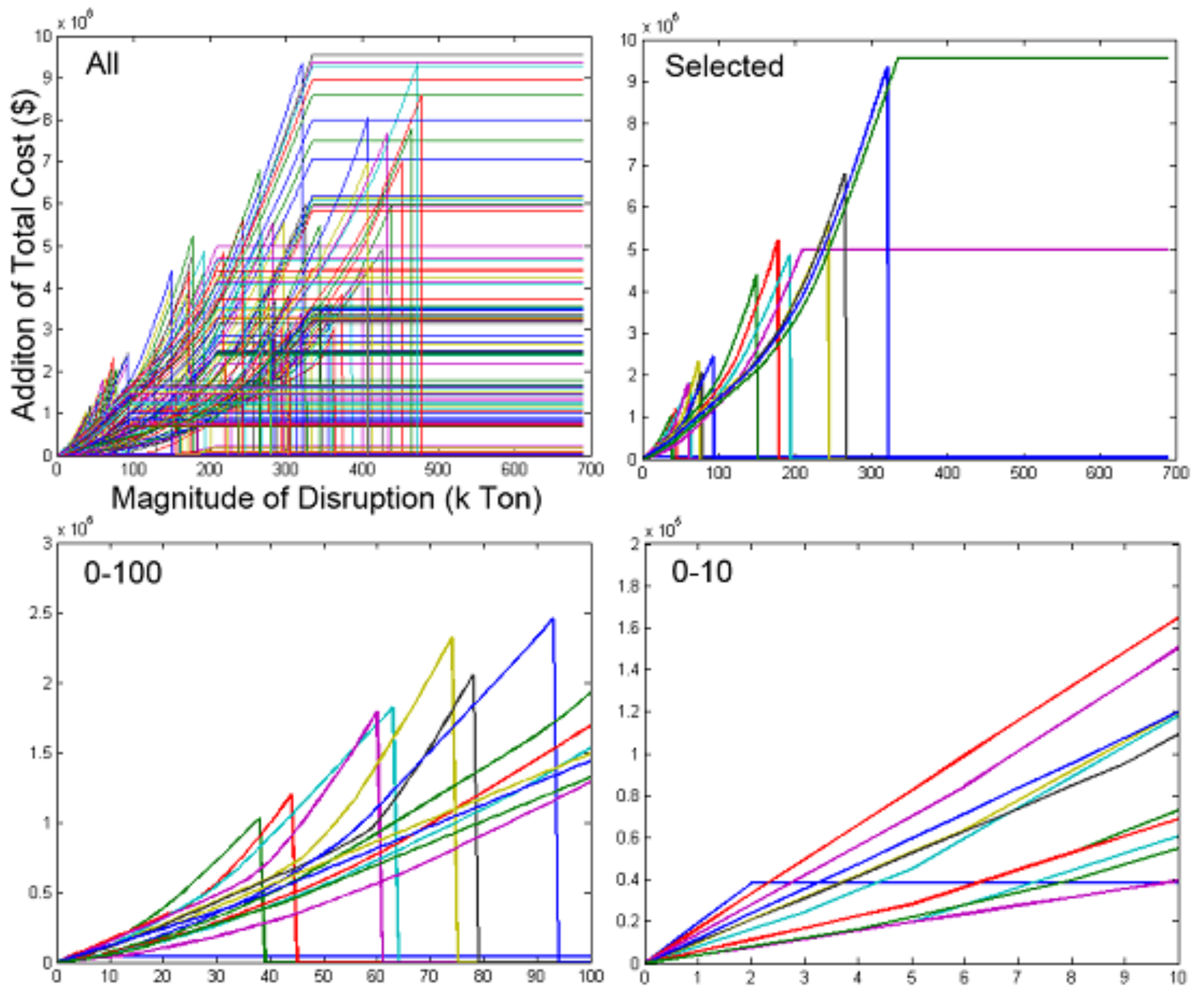


Figure 6. Dynamic Vulnerability Assessment

CONCLUSION

Based on the assessments, the vulnerability of a target is closely related to three factors: redundancy, alternative routes, and time. For example, Dams No. 5 and 4 are the most vulnerable among the six targets, because of high utilization and lack of good alternative routes. Dam No. 3 is less vulnerable than Dam No. 2 because the former one has more alternative routes. Dam No. 1 is less vulnerable because its capacity is not fully utilized and the slack capacity can absorb small disruptions. Dam No. 6 has a limited impact if disrupted due to its small capacity and good alternative routes. In addition, the time when the disruption occurs is also an important factor for determining the vulnerability. If the disruption occurs near the peak season for transportation, the economic impact of the disruption is high.

Hence, the following suggestions are given to reduce the vulnerability of the corn export supply chain: in the long run, decision-makers need to consider expanding the capacity of the critical infrastructure components; in the short run, identifying and establishing good alternative (backup) routes for vulnerable routes and making emergency plans can improve the responsiveness of the system and can reduce the economic loss when disruption occurs.

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